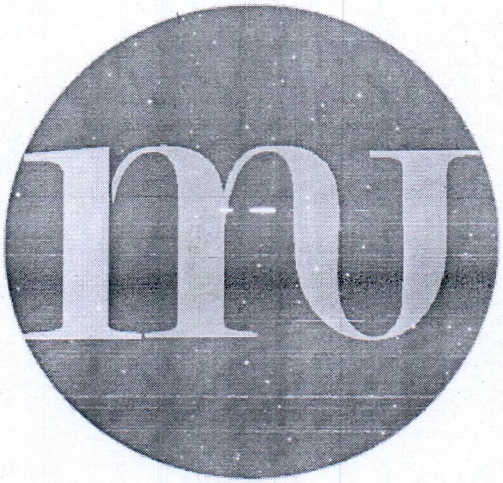
A Comprehensive Report
&
Research Proposal



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Content

S. No.	Topic	Page no.
1	Introduction	01
2	Literature Review	03
3	Research Proposal	05
4	Scope of the work	11
5	Future Scope	11
6	References	12

Introduction:

A signal, technically yet generally speaking, is a a formal description of a phenomenon evolving over time or space; by signal processing we denote any manual or "mechanical" operation which modifies, analyzes or otherwise manipulates the information contained in a signal. Biomedical signals are non-stationary signals whose analysis requires better time and frequency resolution. Such analysis includes, denoising and compression. So, a detailed analysis of the denoising and compression process of various wavelet families and biomedical signals such as Electrocardiogram (ECG), Electromyography (EMG) and Electroencephalography (EEG).

Digital Signal Processors (DSP) take real-world signals like voice, audio, video, temperature, pressure, or positions that have been digitized and then mathematically manipulate them. A DSP is designed for performing mathematical functions like "add", "subtract", "multiply" and "divide" very quickly. Signals need to be processed so that the information that they contain can be displayed, analyzed, or converted to another type of signal that may be of use. In the real-world, analog products detect signals such as sound, light, temperature or pressure and manipulate them. Converters such as an Analog-to-Digital converter then take the real-world signal and turn it into the digital format of 1's and 0's. From here, the DSP takes over by capturing the digitized information and processing it. It then feeds the digitized information back for use in the real world. It does this in one of two ways, either digitally or in an analog format by going through a Digital-to-Analog converter. All of this occurs at very high speeds. A DSP's information can be used by a computer to control such things as security, telephone, home theater systems, and video compression. Signals may be compressed so that they can be transmitted quickly and more efficiently from one place to another (e.g. teleconferencing can transmit speech and video via telephone lines). Signals may also be enhanced or manipulated to improve their quality or provide information that is not sensed by humans (e.g. echo cancellation for cell phones or computer-enhanced medical images). Although real-world signals can be processed in their analog form, processing signals digitally provides the advantages of high speed and accuracy.

1.1. Scheme for the digital processing of an analog signal:

The process of generating a discrete-time signal from the analog signal is shown in block diagram. In the digital signal processing course we are mostly dealing with *discrete-time* rather than *digital* signals and systems, the latter is a subset of the former.

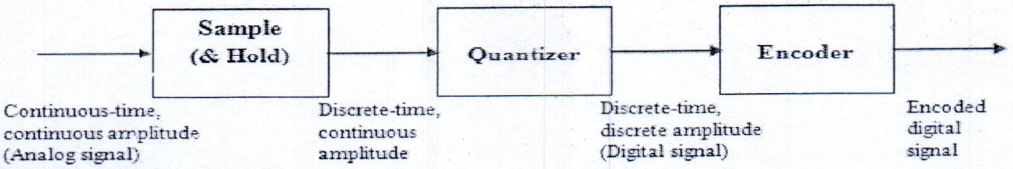

Fig.1.1. Scheme for the digital processing of an analog signal

The 3 boxes shown in the fig.1.1 can be represented by an analog to digital converter (ADC). A complete digital signal processing (DSP) system comprises of an ADC, a DSP algorithm

(for example a difference equation) and a digital to analog converter (DAC) which is shown in fig.1.2.

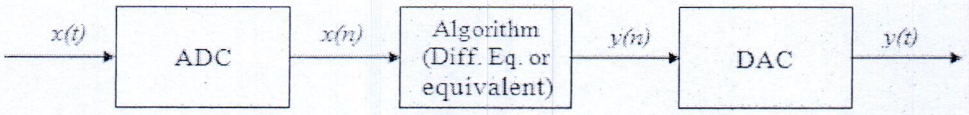

Fig.1.2. Digital Signal Processing System

As the name implies discrete-time signals are defined only at discrete instants of time. Discrete-time signals can arise by sampling analog signals such as a voice signal or a temperature signal in telemetry. Discrete-time signals may also arise naturally, e.g., the number of cars sold on a specific day in a year, or the closing DJIA figure for a specific day of the year.

What's Inside a DSP?

A DSP contains these key components:

- **Program Memory**: Stores the programs the DSP will use to process data
- **Data Memory:** Stores the information to be processed
- **Compute Engine:** Performs the math processing, accessing the program from the Program Memory and the data from the Data Memory
- **Input/Output:** Serves a range of functions to connect to the outside world

Advantages of DSP:

- Less sensitivity to component tolerances and environmental changes
- Volume production without the need for the adjustment during construction or use.
- Amenable to full integration
- Accuracy is more as wordlength increases.
- Easy adjustment of processor characteristic by changing coefficient

- Exact in linear phase
- Multirate processing
- No loading problem due to cascading
- Easy storage in tapes, disks for as long as we like
- Very low frequency with ease(No Problems)

Disadvantages:

- Increased complexity (Sample and Hold, Analog to Digital Converter and Digital to Analog Converter)
- Frequency range is limited due to S/H, A/D, the speed is limited.
- Sampling frequency increases, resolution of A/D converter decreases
- Power dissipation

Literature Review:

We performed an extensive literature review focused on denoising of a weak signal using an appropriate technique and year of publication, comprising studies published from 1990 to 2015.

We examined over 20 papers among 50 selected; emphasizing the search for appropriate techniques used for denoising of a weak signal especially those based on wavelet.
Wavelet transform (WT), due to its sparsity, locality, and multi-resolution nature, has emerged as a simply yet effective de-noising tool. Wavelet packet transform, Coif wavelet, lifting wavelet transform are also used as denoising tool. Much related work has been carried out for applications in de-noising weak signals and evaluated the performance of different wavelet-based and wavelet packet-based thresholding methods for removing noise from the ECG. Suyi Li, Guangda Liu and Zhenbao Lin [1] proposed de-noising algorithms based on wavelet packet (WPT), lifting wavelet (LWT) and stationary wavelet transform (SWT) for de-noising ECG signals, respectively. In ECG de-noising, the goal is to recover the valid ECG from the undesired artifacts with the minimum distortion for presenting a signal, which allows easy visual interpretation and auto diagnosis. We adopt three de-noising algorithms based on wavelet packet (WPT), lifting wavelet (LWT) and stationary wavelet transform (SWT) for de-noising ECG signals, respectively. Through using simulated and real noisy ECG signals from MIT-BIH database, we evaluate the denoising results by means of SNR and visual inspection, and conclude that SWT algorithm is the suitable one for de-noising ECG signals. Su, L. et al [2] employed

Translation-Invariant (TI) method to de-noise ECG signals. In this paper proposes an improved thresholding de-noising method based on Donoho's method. The advantage of the improved de-noising method is that it may not only remain the geometrical characteristics of the original ECG signal and keep the amplitudes of various ECG waveforms efficiently, but also suppress impulsive noise to some extent. Furthermore, the traditional wavelet thresholding de-noising method causes Pseudo-Gibbs phenomena in Q and S waves of ECG signal due to DWT. In order to suppress Pseudo-Gibbs phenomena in Q and S waves, a new de-noising method combining above improved thresholding with the translation-invariant wavelet transform is proposed in this paper. The experimental results indicate that the proposed methods in the paper are better than traditional wavelet thresholding de-noising methods in aspects of remaining geometrical characteristics of ECG signal and the signal-to-noise ratio (SNR). Jing Jin1[3] proposed the de-noising method based on multivariate empirical mode decomposition (MEMD) is creatively proposed to put use to pulsar signal, filling the void that the previous methods based on the wavelet analysis have the limitations of choosing the basic functions, and the EMD algorithm's bounded that it can't process multiple signals jointly to avoid the mode mixing. MEMD is an extension of EMD, it has the ability to align `common scales' present within multivariate data. Each `common scale' is manifested in the common oscillatory modes in all the variates within an n-variate intrinsic mode function (IMF). These characteristics are especially suitable to process the pulsar signals of multiple channels with inhibition of mode mixing. Comparisons of the SNRs of the de-noised signals with that one generated by standard EMD method support this statement. V.Naga Prudhvi Raj, Dr T Venkateswarlu [4] proposed the denoising method which uses Undecimated Wavelet Transform to decompose the raw ECG signal and we performed the shrinkage operation to eliminate the noise from the noisy signal. In the shrinkage step used semi-soft and stein thresholding operators along with traditional hard and soft thresholding operators and verified the suitability of different wavelet families for the denoising of ECG signals. The results proved that the denoised signal using UDWT (Undecimated Discrete Wavelet Transform) have a better balance between smoothness and accuracy than the DWT. Mohammad Ayat, Mohammad B. Shamsollahi [5] proposed a method for removing white Gaussian noise from ECG signals. Based on wavelet transform and singular points a new method was developed to reduce white noise from ECG signal. Quadratic spline wavelet was used to detect singular points of ECG and thresholds were set to remove noise. Finally the SNR of output signal was evaluated. Objective and visual assessment of the result have shown effectiveness of propose method. Proposed method have been used for denoising ECG signal, However it can be used as general method in other areas of signal processing. The concepts of singularity and local maxima of the wavelet transform modulus were used for analyzing singularity and reconstructing the ECG signal. Adaptive thresholding was used to remove white Gaussian noise modulus maximum of wavelet transform and then reconstruct the signal. Sai,R. et al [6]adopted Db4 lifting wavelet transform to reconstruct ECG signals. An approach is to transmit as much information about the signal as possible, under the constraint of low bandwidth. So, rather than using extracted information about spike instants or spike counts, the goal is defined as using a "lossy"

compression which reduces transferable bits by identifying unnecessary information (i.e., noise) and removing it. This approach enables reconstruction of the whole intracortical signal at a lower bandwidth that allows more advanced spike detection and sorting signal processing algorithms to be utilized at the backend. Among those who selected the latter approach, a group of studies have been performed the intracortical signal compression by using vector quantization (VQ) techniques [7, 8, 9, 10] based on self-organizing maps (SOM) [11]. However, these methods involve a computationally extensive learning procedure and also the performances of these techniques have not been tested under low signal-to-noise ratio (SNR) which is not uncommon condition in intracortical recordings. Wavelet transforms also have been widely used in signal compression [12]. The usefulness of wavelets for data compression and denoising is mainly based on the sparseness capabilities of the transform. Wavelet-based methods need to select a wavelet basis for compression. In most of the wavelet-based compression methods [13, 14, 15, 16], fixed wavelet bases have been used, which are not necessarily optimal for compression. Wavelet packets have been used previously for optimal basis selection in biomedical signal compression [17, 18]; however, some studies have shown that the commonly used entropy cost function for wavelet packet basis selection does not account for the statistical properties of the noise and the sensitivity of the basis search to noise realization can result in highly variable performance [19, 20].

RESEARCH PROPOSAL

Weak Signal analysis using different Technique

Biomedical signals from many sources including heart, brain and endocrine system pose a challenge to researchers who may have to separate weak signals arriving from multiple sources contaminated with artifacts and noise. The analysis of these signals is important both for research and for medical diagnosis and treatment. The main difficulty in dealing with biomedical signals is the extreme variability of the signals and the necessity to operate on case to case basis. Another important aspect of biomedical signals is that the information of interest is often a combination of features that are well localized temporally or spatially and other that are more diffused. This requires the use of analysis methods sufficiently versatile to handle events that can be at opposite extremes in terms of their time-frequency localization. So, a robust method is to be designed which work in most circumstances rather than under very specific assumptions. Biomedical signals due to its enormous virtues are widely applied in several medical applications; Electrocardiogram, Electroencephalogram and Electromyogram are to name a few. However, these signals experience the addition of noise and result in an inefficient performance. Denoising or the removal of noise is hence a major preprocessing task for such signals, and it has been carried out by different schemes for the past few years. Among the several schemes,

wavelet-based denoising has taken the universal place in the signal-processing area. Wavelet transform has been an innovative method for the analysis and processing of non-stationary signals such as bio-signals in which both time and frequency information is vital. From the wide range of applications of wavelets, the most important application is the removal of noise from biomedical signals, which is gifted by thresholding wavelet coefficients in order to separate signal from noise. In the present work a combined scheme of applying denoising and compression for biomedical signals has been presented. Using traditional methods, it is hard to eliminate the noises present in the signals. A detailed analysis of Discrete Wavelet Transform (DWT) denoising using various wavelet families on biomedical signals (ECG, EMG and EEG) is presented in the thesis. The main intention of the work is to explore the wavelet function that is optimal in identifying and denoising the various biomedical signals. Nevertheless, Wavelet transforms offer better results for denoising the bio-medical signals, identification of the optimal Wavelet type is crucial. The proposed Wavelet Transform based frequency thresholding is used for noise removal of the noise corrupted decomposed biomedical signals. Then the signal is reconstructed using inverse wavelet reconstruction method. To reduce the storage size, hybrid wavelet Shannon-Fano coding is used for compression of denoised signal. Efficiency of the method used for existing techniques for the denoising of ECG, EEG and EMG signals will be evaluated and compared in terms of Signal to Noise Ratio (SNR), Percent Root Mean Square Difference (PRD), Mean Square Error (MSE) and Compression Ratio (CR). The biomedical signals are recorded, they need to be analysed. The major operations of signal processing include:

1) Signal acquisition and reconstruction,
2) Quality improvement including filtering, smoothing and digitization,
3) Feature extraction,
4) Signal compression,
5) Prediction.

In other words, the analysis includes, information gathering i.e. inferring a system by phenomena measurement, diagnosis of malfunction or deformity and monitoring the system for continuous or periodic information. From the literature it is obvious that there is a strong need of an efficient classifier for deciding the optimal wavelet family for denoising different biomedical signals. Since each biomedical signal has its unique nature and characteristics, the classifier must be trained in an efficient way with the nature of each signal for accurate classification of optimal wavelet. Moreover we are in need of an effective biomedical signal compression algorithm achieving best CR and PRD values.

Based upon the above listed directions, the problem for this work is formulated as:

- To find the optimal wavelet for biomedical signal.
- To focus on reducing time and storage space, however at the same time signals must be denoised efficiently with the optimal wavelet.

Once the optimal wavelet is found, biomedical signals will be denoised using this wavelet with focus on reducing time and storage space. Biomedical signals considered will be ECG, EEG and EMG.

The main motive of the thesis lies on denoising signals with the most suitable wavelet, which is classified using Artificial Neural network. It results in less overhead time, since the classification algorithm is already trained for almost all of the members of wavelet family. Moreover a hybrid compression algorithm is applied after the denoising process and thus a less space is needed for storing compressed information and is used for reconstruction of the original signal. Thus the objectives of minimum space and less time are achieved in the thesis only by using simple methods for denoising, classification and compression. The following steps will be carried out to achieve the objectives:

- Discrete Wavelet Transformation for the signals will be applied, which will be performed by means of a low pass and a high pass filter, yielding approximation and detailed coefficients respectively. This process continues for a fixed number of decomposition levels.
- The signal will be decomposed using the Shift Invariant method.
- Then for each level of decomposition, the wavelet frequency thresholding for the detailed and approximation coefficients will be applied resulting in denoised signal.
- The artificial neural network will be trained initially with the properties of each wavelet and the nature of the biomedical signals. By using the parameters the optimized wavelet transform will be selected which is best suitable for denoising using the neural network classifier.

As there is a strong need of an effective biomedical signal compression algorithm for achieving the best CR and PRD values. For this purpose, both using appropriate algorithm and wavelet transform will be combined. The signals obtained after classifications will then be compressed using hybrid wavelet appropriate algorithm.

DIFFERENT DENOISING TECHNIQUES

(i) **Empirical Mode Decomposition (EMD):** In this method the noisy ECG signal is decomposed in to different intrinsic mode functions (IMFs) .Then we must find the width of the QRS complex, to preserve it. Therefore sum of first 3 IMFs were taken and their sum is calculated. With the help of this and R point location QRS width is calculated. Then an adaptive window (Tapered cosine window) of size equal to width of the QRS complex is designed to preserve the QRS complex from the noisy IMFs. Mainly lower order IMFs are noisy. Then the signal can be reconstructed by adding these windowed IMFs and the remaining IMFs [47]. An enhancement to this method can be done by using a moving average filter for the smoothening of windowed

IMFs. Thus we have to increase the QRS complex quality. Here residue got after empirical mode decomposition is also considered. EMD is an adaptive and data driven technique, thus suitable for any non stationary signal [48].And the denoised ECG signal is very much similar to the original clean ECG signal. The ECG signal with high frequency Additive white Gaussian noise can be reduced using this technique.

(ii) **Filtering Techniques**: –The stationary power line interference can be removed using a notch filter. If a notch filter has higher attenuation level, it will be able to remove PLI noise to a greater extent from ECG signal [49].But practically it eliminates power line interference at 50Hz frequency.

(iii) **Discrete Wavelet Transform (DWT)**:- Wavelet transform (WT) is a powerful method for analyzing non stationary signals. ECG signals are time varying and non-stationary signals so WT is suitable for analyzing ECG signal. Wavelets allow both time and frequency analysis of signals. Discrete Wavelet Transform (DWT) analyze and a signal as a linear combination of the sum of the product of the wavelet coefficients and mother wavelet. Generally 3 procedures are done in DWT 1. DWT is applied to the Noisy ECG signal to produce noisy wavelet coefficients 2. Thresholding of the DWT coefficients 3. Inverse wavelet transforms of the threshold wavelet coefficients to obtain denoised ECG signal.

(iv) **Filtered Residue (FR) Method**: In this method the residue of the noisy ECG signal is calculated. The residue is given as the difference between the input ECG signal and the corresponding signal average at every point. This residue is then given to the Low pass FIR filter, thus we get a filtered residue .To reconstruct the final output this filtered residue should be added with the signal average. The main advantages of this algorithm are simple to implement, stable, output is an accurate reconstruction of the actual signal, it preserves high frequency components, and it is fast. The main limitation of the filtered residue algorithm is that the misalignment of the beats has a blurring effect on the output and the FR algorithm is not iterative that is if it is applied to a signal, the measurement of the activation time in the output is not improved [50]

DIFFERENT PERFORMANCE EVALUATION PARAMETERS OF WEAK SIGNAL DENOISING TECHNIQUES:

(i) Signal to Error Ratio (SER)
(ii) Signal to Noise Ratio (SNR)
(iii) Signal to noise ratio improvement (SNR imp): should be larger for a better denoising method.
(iv) Mean square error (MSE): MSE should be small for better denoising technique.
(v) Percentage Root mean square Difference (PRD): Denoising technique said to be better if it has a smaller PRD value.

Theory of Multirate Signal Processing with Application to Signal Reconstruction

Signal processing methods for signals sampled at different rates are investigated and applied to the problem of signal reconstruction. The problem is approached from the viewpoint of linear mean-square estimation theory and multirate signal processing for one and two dimensional signals. A new look is taken at multirate system theory in one and two dimensions which provides the framework for these methodologies. A careful analysis of linear optimal filtering for problems involving different input and output sampling rates is conducted. These results in the development of index mapping techniques that simplify the formulation of Wiener-Hopf equations whose solution determine the optimal filters. The required filters exhibit periodicity in both one and two dimensions, due to the difference in sampling rates. The reconstruction algorithms are applied to one and two-dimensional reconstruction problems. Multirate signal processing theory deals with the analysis of a system comprised of multiple signals at different sampling rates and are fundamental to this research. An example of such a system is a sensor network that collects and processes data from various sensors, where the information from each sensor might be collected at a different rate. In developing this theory, a number of relationships between signals in a multirate system are identified. The critical finding is that all of the signals in a multirate system can be referred to a single "universal" rate for that system; therefore, many of the results of standard signal processing theory can be adapted to multirate systems through this observation. The multirate theory developed here is applied to signal estimation, where one signal is estimated from some other related signal or signals. The desired signal may be corrupted by distortion or interference and is usually unobservable (at least at the moment when the estimate is desired). A typical signal estimation application is the recovery of a transmitted signal from a received signal that has been subject to distortion and is corrupted by noise.

MIMO-OFDM Systems

In any communication system, the emphasis is on estimating the channel response so as to retrieve the transmitted input signal accurately at the receiver's end. Channel Equalisation at the transmitter refers to pre-distorting the input signal so that the effect of the channel is nullified during transmission. This approach works out for slow fading channels where the channel response remains almost constant for a considerable amount of time (coherence time). Our prime objective in this work is to adapt a filter with impulse response (F) to the channel impulse response (H) at the transmitter end. By evaluating the inverse of the filter and passing the symbols through a filter designed with frequency response, we can equalise the distortions on the input due to channel.

when this technique is implemented for basic modulation schemes like PAM or QAM. Whereas, when the technique is implemented for Multiple Input Multiple Output (MIMO) system, or a Multiple Input Multiple Output (MIMO) system with Orthogonal Frequency Division

Multiplexing (OFDM) modulation, it shows a better Bit Error Rate (BER) performance than that of the usual way of channel equalization in the respective systems.

MIMO

MIMO technology has attracted attention in wireless communications. MIMO systems have various advantages over SISO systems:

1. Significant increases in data transmission without additional bandwidth or transmit power. It achieves this by higher spectral efficiency (more bits per second per hertz of bandwidth) and link reliability or diversity (reduced fading).

2. No need to alter the common air interface while upgrading.

3. By various coding techniques, depth and duration of fades are reduced.

These properties make MIMO a hot research area in the field of communication and signal processing. Though MIMO's diversity fights multipath well, it could be still more enhanced by combining it with some special techniques: Orthogonal Frequency Division Multiplexing (OFDM) and OFDM and WPMCM counter Inter-symbol interference (ISI) in mobile communications.

OFDM

OFDM is a multicarrier modulation technique in which the available channel is split up into several sub-channels and symbols are transmitted using different subcarriers. Here the signal processing is made digitally in the frequency domain by using the – IFFT/FFT blocks. Guard time is added to reduce the effects caused by multipath propagation. With a simple implementation spectral efficiency and tolerance to ISI is achieved

MIMO-OFDM

OFDM transforms a frequency selective channel into a large set of individual frequency non-selective narrowband channels, which is suited for a MIMO structure that requires a frequency non-selective characteristic at each channel when the transmission rate is high enough to make the whole channel frequency selective. Therefore, a MIMO system employing OFDM, denoted MIMO-OFDM, is able to achieve high spectral efficiency. However, the adoption of multiple antenna elements at the transmitter for spatial transmission results in a superposition of multiple transmitted signals at the receiver weighted by their corresponding multipath channels and makes the reception more difficult. This imposes a real challenge on how to design a practical system that can offer a true spectral efficiency improvement. If the channel is frequency selective, the received signals are distorted by ISI, which makes the detection of transmitted signals difficult. OFDM has emerged as one of most efficient ways to remove such ISI.

SYSTEM DESIGN

The system consists of N transmit antennas and M receive antennas. The OFDM signal for each antenna is obtained by using inverse fast Fourier transform (IFFT) and can be detected by fast Fourier transform (FFT). Advantages of this: Less interference, Diversity gain, Increase data capacity, Power efficiency, Bandwidth gain.

SCOPE OF THE WORK

Weak signals are affected by different types of noise and interference as weak signals are very sensitive signal. For Example ECG signals are mostly corrupted by colored noise, white noise electrode movement noise, muscle artifact noise, baseline wander, composite noise and power line interference (PLI). Due to these noises and interference correct diagnosis of the ECG signal does not take place. So, it is very important to remove these noises and interference from the ECG signal.

AREA OF INTEREST

(i) Wavelet Transform, Empirical Mode Decomposition, other transform techniques.
(ii) Filtering Techniques
(iii) Multirate systems
(iv) MIMO- OFDM systems

FUTURE SCOPE

The work can be extended in several directions. Here several research directions are presented this might be followed for further applications. The possible improvements that can be brought to the used method are as follows:

- Since the application of wavelet transformation in electro cardiology is relatively new field of research, many methodological aspects (Choice of the mother wavelet, values of the scale parameters) of the wavelet technique will require extra analysis in order to improve the clinical usefulness of this novel signal processing system.
- Simultaneously, diagnostic and prognostic importance of wavelet techniques in various fields of electro cardiology needs to be recognized in large clinical studies.
- Moreover the work can be further improved by developing disease diagnostic clinical applications with the assistance of this novel denoising and compression schemes for EEG and EMG signals.

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